Persistence in the Cryptocurrency Market:

The Impact of the Covid-19 Pandemic and of the Russia-Ukraine War

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Abstract

This paper uses fractional integration methods to analyse persistence in the five cryptocurrencies with the highest degree of market capitalization (Bitcoin, Ethereum, Tether, BNB and USD Coin), and also the possible impact of both the Covid-19 pandemic and the Russia-Ukraine war. The findings suggest mean reversion in the case of the USD Coin, an explosive pattern in the case of BNB, and anti-persistence in the case of Tether. The unit root null hypothesis cannot be rejected in the case of Bitcoin, Ethereum and USD Coin, whilst it is rejected in favour of $d > 1$ in the case of BNB (where d is the fractional differencing parameter measuring persistence). Finally, there is not much evidence that either the Covid-19 pandemic or the Russia-Ukraine conflict have significantly affected persistence in the cryptocurrency market.

Keywords: cryptocurrency; persistence; long memory; fractional integration

JEL Classification: C22, G12

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1. Introduction

The cryptocurrency market has developed significantly since the launch of Bitcoin in January 2009, thereby providing new investment opportunities to agents. One important issue is the extent to which it can be characterised as an efficient market, which requires prices to follow a random walk and thus to be unpredictable. Whilst numerous studies have analysed persistence of other asset prices (see, e.g., Mills, 1993; Barkoulas & Baum, 1996; Jacobsen, 1996; Caporale and Gil-Alana, 2004; Caporale et al., 2016), the evidence concerning the cryptocurrency market is more limited. The most extensive study on this topic is due to Caporale et al. (2018), who found time-varying persistence in Bitcoin, Litecoin, Wave, and Run over the period 2013-2017, whilst Caporale and Plastun (2019) detected an anomaly in the case of Bitcoin, which appears to have higher returns on Mondays than on the other days of the week.

The aim of the present paper is to investigate the possible impact on the cryptocurrency market of two most recent exogenous shocks that have affected the world economy, namely the Covid-19 pandemic and the Russia-Ukraine war. Although a few existing studies have already examined this issue (see, e.g., Sabrine et al., 2022; Khalfaoui et al., 2023; Lahmiri, 2023; Theiri et al., 2023), ours considers a wider set of cryptocurrencies and uses a more general and flexible modelling approach. More specifically, our analysis is carried out for the five cryptocurrencies with the highest degree of market capitalisation (Bitcoin, Ethereum, Tether, BNB and USD Coin) using fractional integration methods that are informative about the long-memory, mean reversion and persistence properties of the series of interest. Estimates of the fractional differencing parameter measuring the degree of persistence are obtained first for the period ending in December 2019; then the sample is extended to December 2021 to examine the possible impact of the Covid-

19 pandemic, and finally to April 2023 to shed light on the possible effects of the Russia-Ukraine conflict as well.

The layout of the paper is the following: Section 2 briefly reviews the relevant literature; Section 3 presents the empirical analysis; Section 4 offers some concluding remarks.

2. Literature Review

Despite the relatively recent launch of cryptocurrencies, their considerable success has led to various studies being carried out on the properties of this new market. For instance, Giudici et al. (2020) highlighted some of the benefits of cryptocurrencies but also stressed the need for more stringent regulations. Papadimitriou et al. (2020) found that the cryptocurrencies with the highest market capitalisation are not necessarily those offering the most profitable investment opportunities. Gil-Alana et al. (2020) could not detect long-run linkages between the main cryptocurrencies. Colon et al. (2021) concluded that cryptocurrencies are used as a strong hedge in the presence of geopolitical risk and as a weak one in the presence of economic uncertainty. Liu and Serletis (2019) provided evidence of high volatility in the cryptocurrency market resulting from external shocks.

Some other studies have focused on the long-memory properties of cryptocurrencies. For instance, Jena et al. (2020) analysed time-varying long memory in six cryptocurrencies using the Hurst exponent method and found that DASH, NEW and Bitcoin are the most inefficient cryptocurrency markets. Jiang et al. (2018) also used the Hurst exponent approach and found evidence of long memory and inefficiency in the Bitcoin market. Al-Yahyaee et al. (2020) applied the MF-DFA method in addition to the Hurst exponent one and found long memory in six cryptocurrencies. Aslan and Sensoy (2020) again used the Hurst exponent for the most capitalised cryptocurrencies and found considerable heterogeneity across these markets. Finally, Arouxet et al. (2022) reported that the Covid-19 pandemic had only a slight impact on the long-memory properties of both the returns and volatility of seven cryptocurrencies.

3. Empirical Analysis

The present study uses daily data on the five cryptocurrencies with the highest market capitalization, namely Bitcoin, Ethereum, Tether, BNB and USD Coin. The sample period ends in all cases on 25 April 2023, while the start date varies depending on data availability (see Table 1 for details). The longest available series is for Bitcoin (from 28 April 2013), which is also the leader in the cryptocurrency market in terms of market capitalisation (more than double that of Ethereum). Plots of the five series are displayed in Figure 1.

TABLE 1 AND FIGURE 1 ABOUT HERE

The estimated model is the following:

$$y_t = \alpha + \beta t + x_t, \qquad (1 - B)^d x_t = u_t, t = 1, 2, \ldots, \tag{1}$$

where y_t is the observed time series, α and β are the intercept and the time trend coefficient respectively, d stands for the differencing parameter measuring persistence, and u_t is a I(0) or short-memory process which is assumed to be weakly autocorrelated; however, instead of imposing a specific ARMA model, we use the exponential spectral model of Bloomfield (1973), which is a non-parametric approach approximating AR structures. This type of model has also been used to analyse the properties of various other asset prices (see, e.g., Gil-Alana and Moreno, 2012; Nystrup et al., 2017; Abbritti et al., 2016; 2023; etc.).

Table 2 reports the estimates of d and the 95% confidence bands for the sample ending in December 2019, i.e., prior to the Covid-19 pandemic, whilst the results in Table 3 are for the sample ending in December 2021 which incorporates the pandemic, and those in Table 4 for the one ending on 25 April 2023 which also includes the Russia-Ukraine war. In each case three difference specifications are estimated: (i) without deterministic terms, (ii) with a constant only, (iii) with a constant and a linear time trend. The estimates in bold are those from the models selected on the basis of the statistical significance of the regressors.

INSERT TABLES 2, 3 AND 4 ABOUT HERE

In the case of the sample ending in December 2019 (Table 2) the time trend is significant for Tether, while the intercept is significant for the other cryptocurrencies. The estimated values of d are close to 1 in three out of the five cases, the exception being USD Coin ($d = 0.52$) and Tether (-0.11), the latter being characterised by anti-persistence ($d < 0$). The unit root null hypothesis cannot be rejected for Bitcoin ($d = 1.01$) and Ethereum (1.02), while it is rejected in favour of $d > 1$ for BNB ($d = 1.14$).

When the sample is extended to December 2021 to include the Covid-19 pandemic (Table 3), the time trend coefficients is found to be significant for three cryptocurrencies (Bitcoin, Ethereum and Tether), while the intercept is significant for the other two (BNB and USD Coin). The estimates of d are now higher, and in the case of BNB the unit root null is rejected in favour of $d > 1$, whereas for USD it cannot be rejected ($d = 1$), and in the case of Tether again anti-persistence ($d < 0$) is found.

Finally, in the case of the sample ending in April 2023, which also includes the Russia-Ukraine war (Table 4), the time trend coefficient is statistically significant for Tether, for which anti-persistence is again found ($d<0$), whilst the unit root null ($d=1$) cannot be rejected in the case of Bitcoin (1.03), Ethereum (1.03) and USD Coin (0.55), but it is rejected in favour of $d > 1$ in the case of BNB (1.15).

INSERT TABLE 5 ABOUT HERE

Table 5 provides a summary of the results. We indicate with " + " and " – " respectively an increase and decrease in the degree of persistence with respect to the previous subsample. Apart from Tether, which is characterised by anti-persistence, the only series exhibiting mean-reverting behaviour is USD Coin, for which the full-sample estimate of d is lower than 1 (0.55), whilst shocks are found to have permanent effects in the cases of Bitcoin, BNB and Ethereum, for which the estimates of d are significantly higher than 1. On the whole, the evidence also suggests very limited effects of both the Covid-19 and the Russia-Ukraine war on the degree of persistence of the cryptocurrency market. The most significant impact is detected in the case of USD Coin, the estimated value of d increasing from 0.52 to 0.56 when including the Covid-19 pandemic period and then decreasing slightly to 0.56 when also incorporating the Russia-Ukraine conflict. A slight increase in d is found in the case of BNB and Ethereum in the two extended samples compared to the shortest one (from 1.14 to 1.15, and from 1.02 to 1.03), whilst there is a slight decrease in the case of Bitcoin in the full sample compared to the two earlier ones (from 1.04 to 1.03), and in the degree of anti-persistence of Tether (from -0.09 to -0.08) in the two extended samples. However, in all cases the differences between these point estimates are not statistically significant.

The closest study to the current one is Caporale et al. (2018), which investigates the persistence of four main cryptocurrencies (Bitcoin, Litecoin, Ripple, Dash) over the sample period 2013–2017. Interestingly, their recursive analysis also implies that in the case of Bitcoin the parameter d is greater than 1, which is consistent with our findings.

5. Conclusions

This paper has applied fractional integration techniques to analyse persistence in the five cryptocurrencies with the highest market capitalisation, namely Bitcoin, Ethereum, Tether, BNB and USD Coin, and also considered the possible impact of the Covid-19 pandemic and of the Russia-Ukraine war. Our results point to mean reversion in the case of the USD Coin ($0.5 \leq d < 1$), an explosive pattern ($d > 1$) in the case of BNB, and anti-persistence ($d < 0$) in the case of Tether. The I(1) null hypothesis cannot be rejected in the case of Bitcoin (1.03), Ethereum (1.03) and USD Coin (0.55), whilst it is rejected in favour of $d > 1$ in the case of BNB (1.15). A comparison of the estimates obtained for different sample periods indicates a very limited impact (if any) of both the Covid-19 pandemic and the Russia-Ukraine conflict on persistence in the cryptocurrency market.

One limitation of the present study is that it does not take into account possible nonlinearities. Future work will address this issue by, for instance, using Chebyshev polynomials in time as in Cuestas and Gil-Alana (2016). Further, it will also examine the possible effects on the cryptocurrency market of other shocks such as the Global Financial Crisis (GFC) of 2007-8.

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Table 1: Capitalisation in the cryptocurrency market (25.04.2023)

#	Name	Market Cap	Price	Circulating Supply	The sample starts from
1	Bitcoin	$577,035,919,211	$28,307.60	19,356,750 BTC	28-Apr-13
2	Ethereum	$234,980,383,693	$1,866.75	120,404,793 ETH	7-Aug-15
3	Tether	$81,573,969,703	$1.0002	81,576,838,534 USDT	25-Feb-15
4	BNB	$53,433,930,952	$338.33	155,863,605 BNB	25-Jul-17
5	USD Coin	$30,684,782,288	$1.0000	30,684,584,879 USDC	8-Oct-18

Source: https://coinmarketcap.com/coins/, Cryptocurrency Market Capitalization Data.

Table 2: Estimates of d for the sample ending in December 2019

Series	No terms	An intercept	An intercept and a time trend
Bitcoin	0.97 (0.93, 1.02)	**1.04 (1.00, 1.08)**	1.04 (1.00, 1.08)
BNB	1.07 (0.99, 1.18)	**1.14 (1.06, 1.23)**	1.14 (1.06, 1.22)
Ethereum	1.04 (0.99, 1.09)	**1.02 (0.98, 1.07)**	1.02 (0.98, 1.07)
Tether	-0.09 (-0.13, -0.06)	-0.09 (-0.13, -0.06)	**-0.11 (-0.15, -0.08)**
USD Coin	0.57 (0.48, 0.67)	**0.52 (0.43, 0.63)**	0.50 (0.41, 0.63)
Estimated coefficients in the selected models:			
Series	d	Intercept	Intercept and time trend
Bitcoin	1.04 (1.00, 1.08)	4.8995 (114.99)	---
BNB	1.14 (1.06, 1.23)	-2.2152 (-29.02)	---
Ethereum	1.02 (0.98, 1.07)	1.0169 (13.73)	---
Tether	-0.11 (-0.15, -0.08)	-0.00275 (-6.54)	0.0000034 (8.00)
USD Coin	0.52 (0.43, 0.63)	0.00704 (2.53)	---

Note: values in parenthesis in the upper panel are the 95% confidence intervals for the estimates of the differencing parameter. In bold, the estimates from the selected models. In the lower panel, in parenthesis in column 3 and 4, the corresponding t-values.

Table 3: Estimates of d with data ending at December 2021

Series	No terms	An intercept	An intercept and a time trend
Bitcoin	0.98 (0.95, 1.01)	1.04 (1.01, 1.09)	**1.04 (1.01, 1.09)**
BNB	1.10 (1.03, 1.17)	**1.15 (1.09, 1.22)**	1.15 (1.09, 1.21)
Ethereum	1.04 (1.00, 1.09)	1.03 (0.99, 1.08)	**1.03 (0.99, 1.08)**
Tether	-0.08 (-0.11, -0.05)	-0.08 (-0.11, -0.05)	**-0.09 (-0.12, -0.05)**
USD Coin	0.58 (0.53, 0.66)	**0.56 (0.48, 0.64)**	0.55 (0.49, 0.64)
Estimated coefficients in the selected models:			
Series	d	Intercept	Intercept and time trend
Bitcoin	1.04 (1.01, 1.09)	4.8991 (115.99)	0.0018 (1.76)
BNB	1.15 (1.09, 1.22)	-2.2152 (-31.51)	---
Ethereum	1.03 (0.99, 1.08)	10.260 (14.98)	0.0030 (1.68)
Tether	-0.09 (-0.12, -0.05)	-0.00116 (-3.52)	0.0000011 (5.01)
USD Coin	0.56 (0.48, 0.64)	0.00597 (2.26)	---

Note: values in parenthesis in the upper panel are the 95% confidence intervals for the estimates of the differencing parameter. In bold, the estimates from the selected models. In the lower panel, in parenthesis in column 3 and 4, the corresponding t-values.

Table 4: Estimates of d with data ending at December 2023

Series	No terms	An intercept	An intercept and a time trend
Bitcoin	0.99 (0.95, 1.04)	**1.03 (0.99, 1.07)**	1.03 (0.99, 1.07)
BNB	1.09 (1.03, 1.16)	**1.15 (1.10, 1.21)**	1.15 (1.10, 1.21)
Ethereum	1.04 (1.00, 1.08)	**1.03 (0.99, 1.07)**	1.03 (0.99, 1.07)
Tether	-0.08 (-0.11, -0.05)	-0.08 (-0.11, -0.06)	**-0.08 (-0.11, -0.05)**
USD Coin	0.57 (0.52, 0.63)	**0.55 (0.49, 0.61)**	0.54 (0.49, 0.61)
Estimated coefficients in the selected models:			
Series	D	Intercept	Intercept and time trend
Bitcoin	1.03 (0.99, 1.07)	6.7060 (174.99)	---
BNB	1.15 (1.10, 1.21)	-2.2152 (-34.59)	---
Ethereum	1.03 (0.99, 1.07)	10.289 (15.88)	---
Tether	-0.08 (-0.11, -0.05)	-0.00062 (-2.15)	0.0000005 (3.39)
USD Coin	0.55 (0.49, 0.61)	0.00584 (2.63)	---

Note: values in parenthesis in the upper panel are the 95% confidence intervals for the estimates of the differencing parameter. In bold, the estimates from the selected models. In the lower panel, in parenthesis in column 3 and 4, the corresponding t-values.

Table 5: Summary of the Results

Series	Pre-Covid-19	Covid-19	Russia-Ukraine war
Bitcoin	1.04 (1.00, 1.08)	1.04 (1.01, 1.09)	1.03 (0.99, 1.07)$^{-}$
BNB	1.14 (1.06, 1.23)	1.15 (1.09, 1.22)$^{+}$	1.15 (1.10, 1.21)
Ethereum	1.02 (0.98, 1.07)	1.03 (0.99, 1.08)$^{+}$	1.03 (0.99, 1.07)
Tether	-0.09 (-0.13, -0.06)	-0.08 (-0.11, -0.05)$^{+}$	-0.08 (-0.11, -0.06)
USD Coin	0.52 (0.43, 0.63)	0.56 (0.48, 0.64)$^{+}$	0.55 (0.49, 0.61)$^{-}$

Note: - and + indicate respectively a decrease and an increased in the order of integration with respect to the previous subsample.

Figure 1: Time series plots